



# Current and future assessments of soil erosion by water on the Tibetan Plateau based on RUSLE and CMIP5 climate models

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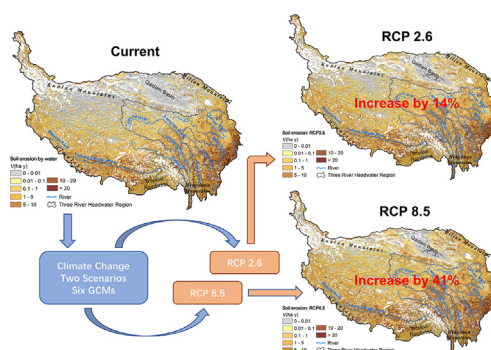
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## HIGHLIGHTS

- Present soil erosion by water on the Tibetan Plateau was predicted.
- The impact of the climate change was evaluated and incorporated into the prediction of *R* factor in 2050.
- Erosion rate in 2050 was estimated with the corresponding projected *R* factor and other erosion factors.
- Estimated erosion rates in 2050 could potentially increase by 14% to 41% from current rates.

## GRAPHICAL ABSTRACT



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## ABSTRACT

Soil erosion by water is accelerated by a warming climate and negatively impacts water security and ecological conservation. The Tibetan Plateau (TP) has experienced warming at a rate approximately twice that observed globally, and heavy precipitation events lead to an increased risk of erosion. In this study, we assessed current erosion on the TP and predicted potential soil erosion by water in 2050. The study was conducted in three steps. During the first step, we used the Revised Universal Soil Equation (RUSLE), publicly available data, and the most recent earth observations to derive estimates of annual erosion from 2002 to 2016 on the TP at 1-km resolution. During the second step, we used a multiple linear regression (MLR) model and a set of climatic covariates to predict rainfall erosivity on the TP in 2050. The MLR was used to establish the relationship between current rainfall erosivity data and a set of current climatic and other covariates. The coefficients of the MLR were generalised with climate covariates for 2050 derived from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) models to estimate rainfall erosivity in 2050. During the third step, soil erosion by water in 2050 was predicted using rainfall erosivity in 2050 and other erosion factors. The results show that the mean annual soil erosion rate on the TP under current conditions is  $2.76 \text{ t ha}^{-1} \text{ y}^{-1}$ , which is equivalent to an annual soil loss of  $559.59 \times 10^6 \text{ t}$ . Our 2050 projections suggested that erosion on the TP will increase to  $3.17 \text{ t ha}^{-1} \text{ y}^{-1}$  and  $3.91 \text{ t ha}^{-1} \text{ y}^{-1}$  under conditions represented by RCP2.6 and RCP8.5, respectively. The current assessment

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and future prediction of soil erosion by water on the TP should be valuable for environment protection and soil conservation in this unique region and elsewhere.

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## 1. Introduction

Soil erosion by water has become one of the greatest global threats to the environment (Chappell et al., 2016; Navarro-Hevia et al., 2016). As a result of soil erosion by water, soil condition, water quality, species habitats and the provision of ecosystem services are negatively affected (Amundson et al., 2015; Teng et al., 2016). It is important to quantify the impacts of soil erosion by water and to develop effective measures for soil and water conservation. Soil erosion models are often employed to assess the risk of soil loss (Karydas et al., 2014). Among them, the Revised Universal Soil Loss Equation (RUSLE; Renard et al., 1997) has been applied commonly to estimate long-term soil erosion rates from hillslopes in large-scale studies (Panagos et al., 2015; Teng et al., 2016).

The effects of climate change on soil erosion by water have been described by researchers (Garcia-Fayos and Bochet, 2009; Li and Fang, 2016; Yang et al., 2003). The characteristics of rainfall (rainfall amount, intensity and spatio-temporal distribution) directly affect soil erosion. In addition, rising temperature also indirectly affects soil erosion (Li and Fang, 2016). According to the Fifth Assessment Report (AR5) of the IPCC (Intergovernmental Panel on Climate Change), global mean precipitation and surface temperature have changed significantly, and the report suggests that these changes are very likely to continue during the 21st century (IPCC, 2014). The effects are still uncertain; therefore, the magnitude of the effects of climate variability on soil erosion needs to be investigated.

The Tibetan Plateau (TP), which is often known as “the Third Pole” of the Earth (Qiu, 2008), has an average elevation of >4000 m above sea level. The TP, which is also known as the “Asian Water Tower” (Immerzeel et al., 2010), is the source of the region's major river systems and provides water to >1.4 billion people (over 20% of the global population). Soil erosion by water in the TP will not only impact drinking water quality for both people and livestock in downstream rivers but also affect food security in Southeast Asia. Thus, the TP is of immense importance to both the climate and the ecosystems of Asia and the world, and more attention should be paid to the erosion status of these regions (Du et al., 2004; Li et al., 2015).

The TP is affected by regional and global climate change through thermal and mechanical forcing mechanisms (Su et al., 2013), and appears to be particularly sensitive to variations in climate and has become one of the most degraded ecosystems in the world (Baumann et al., 2009). During the 21st century, a warming trend of 0.47 °C (10 yr)<sup>−1</sup> to 0.73 °C (10 yr)<sup>−1</sup> over the TP under the representative concentration pathway 8.5 (RCP8.5) scenario is predicted by the global climate models from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) (Su et al., 2013). Research of soil erosion by water on the TP may provide one of the last remaining chances to study the impact of climate change on water erosion over a large region because many of the natural ecological processes and feedbacks are still intact in this area (Chen et al., 2013). However, erosion prediction and risk assessment for the TP is a great challenge, particularly if associated with climate change.

Soil erosion by water on the TP has been estimated by several scientists, but these have been mostly focused on a catchment (Chaplot et al., 2005; Hren et al., 2007; Jiang and Zhang, 2016) or local scale (Pan et al., 2010; Wang et al., 2014; Xu et al., 2009). Due to the high altitude, harsh weather conditions, and remoteness of the plateau, the quantitative and direct measurements of water erosion over the TP are difficult, expensive, time-consuming and nearly impossible. There is limited knowledge regarding quantitative erosion rates over the whole TP. The lack

of field measurements has created a need to develop new methods to predict soil erosion by water and the impacts of future climate change on erosion in this area. Modelling current and future erosion rates is crucial in an assessment of potential future environmental problems and land degradation on the TP (Wang et al., 2014).

Thus, the aims of this study are as follows: first, to predict the current soil erosion by water on the TP using RUSLE; second, to predict the rainfall erosivity factor value in 2050 with climate projections from six CMIP5 Global climate models (GCMs); and third, to estimate soil erosion by water in 2050 with the corresponding projected rainfall erosivity. Our assumption is that soil erosion by water on the TP is driven largely by climate.

## 2. Materials and methods

In this study, the current soil erosion by water was estimated using RUSLE, where the factors were derived from various points and remote-sensing data sets. The current rainfall erosivity value was modelled using a multiple linear regression (MLR) under current climate conditions. We generalised this model but used the future climate data from six GCMs to predict the rainfall erosivity value in 2050. The potential soil loss in 2050 was then predicted by rainfall erosivity and other erosion factors. We describe our approaches as follows:

### 2.1. RUSLE model

RUSLE is a linear equation used to quantify soil erosion by water from hillslopes (Kinnell, 2010). RUSLE is suitable for predicting long-term soil erosion rates over large areas according to the following equation:

$$A = R \times K \times LS \times C \times P \quad (1)$$

where  $A$  is the average rate of soil erosion by water at each cell ( $t \text{ ha}^{-1} \text{ y}^{-1}$ );  $R$  is the rainfall erosivity factor ( $\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ y}^{-1}$ );  $K$  is the soil erodibility factor ( $t \text{ ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ );  $LS$  is the slope length and steepness factor;  $C$  is the cover management factor; and  $P$  is the support practice factor. We describe the derivation of the factors below.

The  $R$  factor is an indicator of the potential of precipitation to detach and transport soil particles. In this study, daily observed precipitation data provided by the National Climate Centre of the China Meteorological Administration (CMA) and the Tropical Rainfall Measuring Mission (TRMM) were used in our calculation of  $R$ . For the 15-year period from 2002 to 2016, 105 rain gauge stations were available across the TP (Fig. 1). We used rainfall estimates from TRMM 3B42 Version 7, which have a spatial resolution of  $0.25^\circ \times 0.25^\circ$  and a temporal resolution of 3 h (Ma et al., 2017; Teng et al., 2014). The  $R$  factor was calculated following the approach presented in Teng et al. (2017). Collocated cokriging (ColCOK) was used to merge the daily rainfall data from the rain gauge stations and TRMM measurements to improve the quality of the precipitation data. The merged daily rainfall data was then used to calculate  $R$  with a power function model, which has been widely used in China and implemented by the National Water Conservancy Survey (Duan et al., 2016; Teng et al., 2017).

$$R_i = m \sum_{j=1}^k (d_j^i)^n \quad (2)$$

where  $R_i$  is the  $R$  value of the  $i$  half-month ( $\text{MJ mm ha}^{-1} \text{ h}^{-1}$ );  $k$  is the number of days in the  $i$  half-month; and  $d_j^i$  is the effective precipitation for day  $j$  of the  $i$  half-month, which is no  $<12$  mm (Ma et al., 2014). Otherwise,  $d_j^i$  is equal to zero. The parameters  $m$  and  $n$  are defined as follows:

$$m = 21.586 * n^{-7.1891} \quad (3)$$

$$n = 0.8363 + \frac{18.114}{d_{12}} + \frac{24.455}{y_{12}} \quad (4)$$

where  $d_{12}$  is the average daily rainfall ( $>12$  mm), and  $y_{12}$  is the yearly average rainfall for days with rainfall  $>12$  mm.

Annual and monthly  $R$  was aggregated by  $R$  value of each half-month. In this case, the outcome of the  $R$  factor was averaged to obtain the mean  $R$  from 2002 to 2016 at a  $0.25^\circ \times 0.25^\circ$  resolution. We down-scaled the  $R$  factor to 1-km spatial resolution with Random Forest (RF) (Breiman, 2001) using a set of environmental variables at 1-km resolution (see Table 1). RF has been successfully used elsewhere for spatial downscaling and mapping (He et al., 2016; Hutengs and Vohland, 2016; Ibarra-Berastegi et al., 2011; Teng et al., 2018). The 105 rain gauges were randomly separated into a training set (70) and a test set (35) (see Fig. 1) before the application of ColCOK to obtain the merged daily rainfall data. The gauges in the test set were retained and used in

an independent assessment of the performance of the model. The predictive performance of the  $R$  value was estimated by using the relevant statistical indices of the coefficient of determination ( $R^2$ ) and root mean square error (RMSE).

The soil erodibility factor,  $K$ , can be estimated using the EPIC model based on soil texture and soil organic carbon data (Sharpley and Williams, 1990). In this study, these data were collected from 410 soil profiles analysed during the Second National Soil Survey (NSSO, 1993, 1994a, 1994b, 1995a, 1995b, 1996, 1998). The locations of these data are shown in Fig. 1. The  $K$  values at these points were calculated following the recommendations in the EPIC model (Sharpley and Williams, 1990). This model was also used in the National Soil and Water Conservation Survey of China.

$$K = 0.1317 * \left( 0.2 + 0.3 * e^{[-0.0256 * San * (1 - \frac{Sil}{100})]} \right) * \left( \frac{Sil}{Cla + Sil} \right)^{0.3} * \left[ 1 - \frac{0.25 * TOC}{TOC + e^{(3.72 - 2.95 * TOC)}} \right] * \left[ 1 - \frac{0.7 * SN_1}{SN_1 + e^{(22.9 * SN_1 - 5.51)}} \right] \quad (5)$$

where  $San$  is the sand content (0.05–2 mm), in %;  $Sil$  is the silt content (0.002–0.05 mm), in %;  $Cla$  is the clay content ( $<0.002$  mm), in %;  $TOC$  is the soil total organic carbon content, in %; and  $SN_1 = 1 - San/100$ . After multiplying by 0.1317, the  $K$  value is expressed in an SI metric ( $\text{t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ). In this model, the soil texture of the

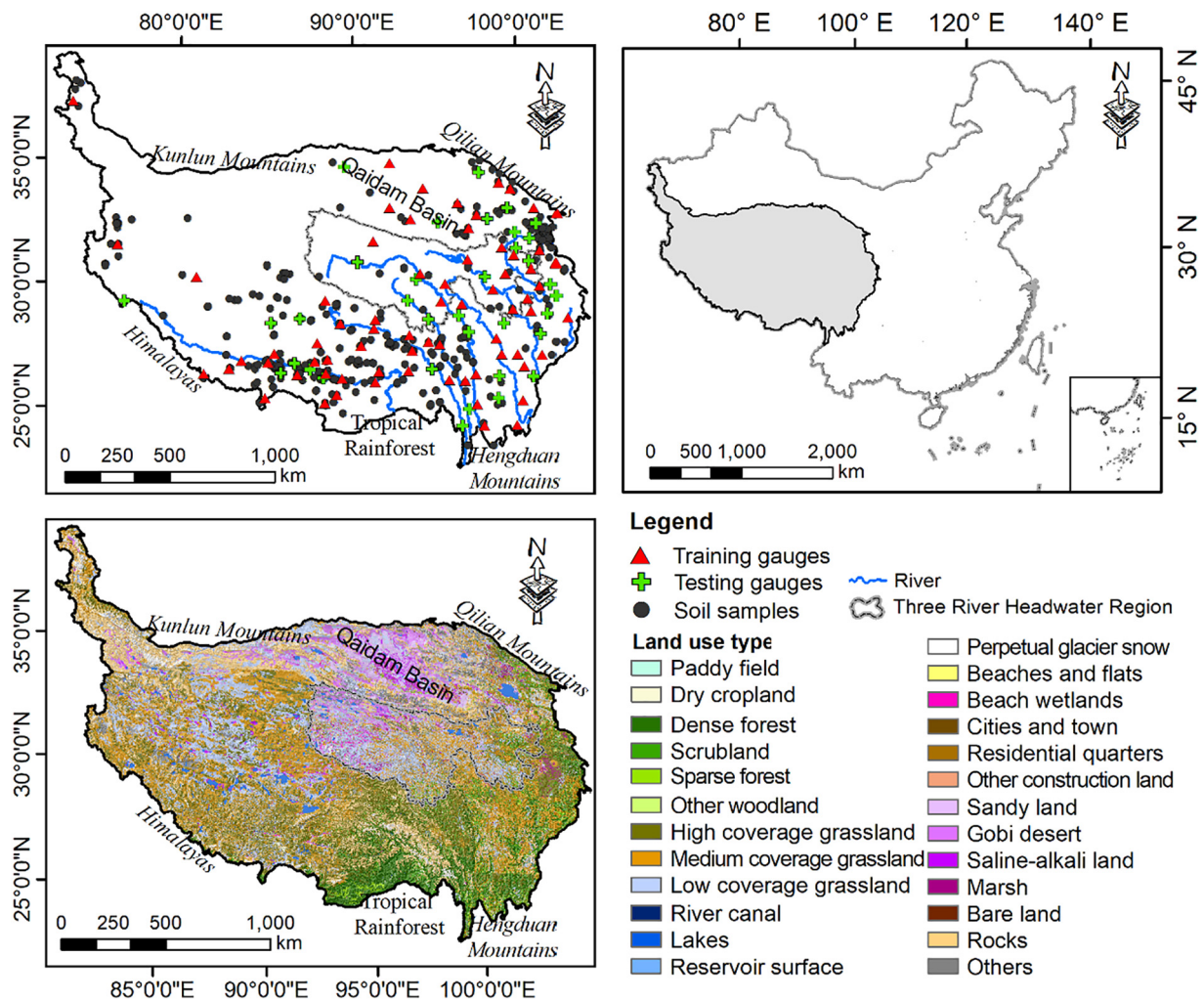


**Fig. 1.** Location of rain gauges and soil samples used in this study across the Tibetan Plateau. The red triangles show the training rain gauges used to estimate annual rainfall erosivity. The green crosses represent testing rain gauge stations used to validate the result of annual rainfall erosivity. The black circles represent the locations for which soil samples were available to estimate soil erodibility. The land use data was provided by the Data Centre for Resources and Environmental Sciences at the Chinese Academy of Sciences (RESDC) (<http://www.resdc.cn>).

**Table 1**

List of the auxiliary environmental predictors in the downscaling model of the rainfall erosivity map and the DSM model of the soil erodibility map.

| Factor     | Environmental variables                 | Resolution | Source                                                                                    |
|------------|-----------------------------------------|------------|-------------------------------------------------------------------------------------------|
| Terrain    | DEM                                     | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
|            | Slope                                   | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
|            | Aspect                                  | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
|            | Curvature                               | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
|            | Roughness Index (TRI)                   | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
|            | Topographic Wetness Index (TWI)         | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
|            | MrVBF                                   | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
| Climate    | Mean annual rainfall (rain)             | 1 km       | China Meteorological Administration (CMA)                                                 |
|            | Mean annual temperature (temperature)   | 1 km       | China Meteorological Administration (CMA)                                                 |
|            | Mean annual solar radiation (radiation) | 1 km       | Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) |
|            | Mean annual evapotranspiration (ET)     | 1 km       | Moderate-resolution imaging spectroradiometer (MODIS)                                     |
|            | Land Surface Temperature_day (LST_d)    | 1 km       | Moderate-resolution imaging spectroradiometer (MODIS)                                     |
|            | Land Surface Temperature_night (LST_n)  | 1 km       | Moderate-resolution imaging spectroradiometer (MODIS)                                     |
|            | Prescott Index (PI)                     | 90 m       | Shuttle Radar Topography Mission (SRTM)                                                   |
| Vegetation | NDVI                                    | 250 m      | Moderate-resolution imaging spectroradiometer (MODIS)                                     |
|            | NPP                                     | 1 km       | Moderate-resolution imaging spectroradiometer (MODIS)                                     |
| Land/Soil  | Land use type (LUCC)                    | 1 km       | Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) |
|            | Soil type                               | 1 km       | Data Center for Resources and Environmental Sciences, Chinese Academy of Sciences (RESDC) |
|            | Sand                                    | 1 km       | Harmonized World Soil Database (HWSD)                                                     |
|            | Silt                                    | 1 km       | Harmonized World Soil Database (HWSD)                                                     |
|            | Clay                                    | 1 km       | Harmonized World Soil Database (HWSD)                                                     |
|            | TOC                                     | 1 km       | Harmonized World Soil Database (HWSD)                                                     |

international system was transformed into the U.S. Department of Agriculture (USDA) system first using a log-linear interpolation method.

The  $K$  values were mapped over the TP at 1-km resolution using the environmental factors that are listed in Table 1 and a digital soil mapping technique (McBratney et al., 2003). It should be noted that the environmental variables of sand, silt, clay and TOC in Table 1 were not included in the  $K$  mapping. The method that we used, which is similar to that described in Teng et al. (2016) and Viscarra Rossel and Chen (2011), is a Cubist regression model. From the 410 data points, we selected at random 136 data points for validation. The other 274 data points were used for training the model, which we assessed using a 10-fold cross validation. To assess its accuracy, the final model was evaluated using the independent validation data set, and we reported the  $R^2$  and RMSE of the predictions.

The  $LS$  factor represents the influence of slope length and slope gradient on soil loss. In this study, we calculated the  $LS$  factor using the 3 arc-second grid Shuttle Radar Topography Mission (SRTM) DEM. The calculation of  $L$  factor was performed using the methodology described in Desmet and Govers (1996).

$$L_{i,j} = \frac{(A_{i,j-in} + D^2)^{m+1} - A_{i,j-in}^{m+1}}{D^{m+2} * x_{i,j}^m * 22.13^m} \quad (6)$$

where  $L_{i,j}$  is the slope length factor from the grid cell with coordinates ( $i, j$ );  $A_{i,j-in}$  is the contributing area at the inlet of the grid cell measured in  $m^2$ ;  $D$  is the grid cell size, in m;  $x_{i,j} = (\sin\alpha_{i,j} + \cos\alpha_{i,j})$ , and  $\alpha_{i,j}$  is the aspect direction for the grid cell with coordinates ( $i, j$ );  $m$  is related to the ratio  $\beta$  of the rill to interrill erosion:

$$m = \frac{\beta}{(1 + \beta)} \quad (7)$$

$$\beta = \frac{(\sin\theta/0.0896)}{[3 * (\sin\theta)^{0.8} + 0.56]} \quad (8)$$

$$S = \begin{cases} 10.8 \sin\theta + 0.03, & \theta < 9^\circ \\ 16.8 \sin\theta - 0.5, & \theta \geq 9^\circ \end{cases} \quad (9)$$

where  $\theta$  is the slope angle.

In this study, the  $LS$  factor was implemented in the System for the Automated Geoscientific Analyses (SAGA) software. The final result of  $LS$  values was resampled to 1-km spatial resolution applying the nearest resampling method in ArcGIS.

The cover management factor,  $C$ , estimates the effects of canopy cover, surface vegetation, surface roughness, prior land use, mulch cover and soil organic material on erosion (Mhangara et al., 2012). These factors would be difficult and costly to measure over the whole

**Table 2**The  $C$  and  $P$  factor values of different land use types on the Tibetan Plateau.

| Land use type             | C value | Reference                                            | P value | Reference                            |
|---------------------------|---------|------------------------------------------------------|---------|--------------------------------------|
| Paddy fields              | 0.1     | Dai et al., 2013; Li et al., 2013; Yang et al., 2003 | 0.01    | Lu et al., 2013; Dai et al., 2013    |
| Dry cropland              | 0.22    | Dai et al., 2013                                     | 0.4     | Xu et al., 2013; Chen and Zha, 2016  |
| Dense forest              | 0.001   | Yang et al., 2003; Bakker et al., 2008               | 1       | Xu et al., 2013; Dai et al., 2013    |
| Shrub forestland          | 0.01    | Teng et al., 2016; Bakker et al., 2008               | 1       | Xu et al., 2013; Dai et al., 2013    |
| Sparse forest             | 0.01    | Yang et al., 2003; Bakker et al., 2008               | 1       | Xu et al., 2013; Dai et al., 2013    |
| Other woodland            | 0.2     | Bakker et al., 2008                                  | 0.7     | Zhang et al., 2016; Dai et al., 2013 |
| High-coverage grassland   | 0.12    | Du et al., 2016; Fu et al., 2005                     | 1       | Zhang et al., 2016                   |
| Medium-coverage grassland | 0.18    | Du et al., 2016; Fu et al., 2005                     | 1       | Zhang et al., 2016                   |
| Low-coverage grassland    | 0.32    | Du et al., 2016; Fu et al., 2005                     | 1       | Zhang et al., 2016                   |
| Sandy land                | 1       | Fagnano et al., 2012                                 | 1       | Sun et al., 2014                     |
| Gobi desert               | 1       | Fagnano et al., 2012                                 | 1       | Sun et al., 2014                     |
| Saline-alkali land        | 1       | Fagnano et al., 2012                                 | 1       | Sun et al., 2014                     |
| Marsh                     | 0.05    | Yang et al., 2003                                    | 1       | Xu et al., 2013                      |
| Bare soil                 | 1       | Li et al., 2013; Dai et al., 2013                    | 1       | Zhang et al., 2016; Dai et al., 2013 |
| Other unused land         | 1       | Du et al., 2016                                      | 1       | Xu et al., 2013                      |

**Table 3**

Conversion of soil erosion rate from erosion grade, with corresponding areas of each erosion grade and its proportion on the Tibetan Plateau. The standard of soil erosion classification was developed by the Ministry of Water Resources of China (SL190-2007).

| Soil loss modules<br>(t ha <sup>-1</sup> yr <sup>-1</sup> ) | Erosion grade               | Area<br>(×10 <sup>4</sup> km <sup>2</sup> ) | Ratio<br>(%) |
|-------------------------------------------------------------|-----------------------------|---------------------------------------------|--------------|
| <5                                                          | Grade 1 (slight)            | 179.49                                      | 76.82        |
| 5–25                                                        | Grade 2 (light)             | 36.59                                       | 15.66        |
| 25–50                                                       | Grade 3 (moderate)          | 9.53                                        | 4.08         |
| 50–80                                                       | Grade 4 (intense)           | 4.66                                        | 1.99         |
| 80–150                                                      | Grade 5 (extremely intense) | 2.98                                        | 1.27         |
| >150                                                        | Grade 6 (severe)            | 0.42                                        | 0.18         |

**Table 4**

List of the auxiliary environmental predictors in the multiple linear regression model.

| Base model<br>(B)/projection<br>model<br>(P) | Factor               | Predictors                              | Resolution | Source    |
|----------------------------------------------|----------------------|-----------------------------------------|------------|-----------|
| BP                                           | Terrain              | DEM (m)                                 | 90 m       | SRTM      |
|                                              |                      | Slope (deg)                             | 90 m       | SRTM      |
|                                              |                      | Aspect (deg)                            | 90 m       | SRTM      |
| B                                            | Climate<br>(current) | Bio-climatic<br>parameters <sup>a</sup> | 1 km       | WorldClim |
| P                                            | Climate<br>(2050)    | Bio-climatic<br>parameters <sup>a</sup> | 1 km       | WorldClim |
| BP                                           | Soil                 | Sand (%)                                | 1 km       | HWSD      |
|                                              |                      | Silt (%)                                | 1 km       | HWSD      |
|                                              |                      | Clay (%)                                | 1 km       | HWSD      |
|                                              |                      | TOC                                     | 1 km       | HWSD      |

<sup>a</sup> Climate data derivatives (WorldClim BioClimatic Parameters, Current and 2050): annual mean temperature (bio1), mean diurnal range (mean of monthly (max temp–min temp)) (bio2), isothermality (bio3), temperature seasonality (standard deviation \* 100) (bio4), maximum temperature of warmest month (bio5), minimum temperature of coldest month (bio6), temperature annual range (bio7), mean temperature of wettest quarter (bio8), mean temperature of driest quarter (bio9), mean temperature of warmest quarter (bio10), mean temperature of coldest quarter (bio11), annual precipitation (bio12), precipitation of wettest month (bio13), precipitation of driest month (bio14), precipitation seasonality (coefficient of variation) (bio15), precipitation of wettest quarter (bio16), precipitation of driest quarter (bio17), precipitation of warmest quarter (bio18), and precipitation of coldest quarter (bio19).

TP and have great variability during the growing season. The support practice factor, *P*, which reflects the effect of contouring and tillage practices (Wischmeier and Smith, 1978), can be estimated based on land use according to the land cover type. In this study, *C* and *P* factors are derived from the best available land cover type for analysing the land cover over the TP, China's 1-km resolution Land-Use/Cover Data set (CLUD; Liu et al., 2010) provided by the Data Centre for Resources and Environmental Sciences at the Chinese Academy of Sciences (RESDC) (<http://www.resdc.cn>). *C* and *P* factor values derived from former studies were used to reclassify the CLUD (Table 2).

**Table 5**

Summary of the six GCMs from CMIP5.

| Model name   | Institution                                                                                                                                                               | Country       | Resolution<br>(longitude × latitude) |
|--------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------|--------------------------------------|
| BCC-CSM1.1   | Beijing Climate Center, China Meteorological Administration                                                                                                               | China         | ~2.8125° × 2.8125°                   |
| GFDL-CM3     | Geophysical Fluid Dynamics Laboratory                                                                                                                                     | United States | 2.5° × 2°                            |
| IPSL-CM5A-LR | L'Institut Pierre-Simon Laplace                                                                                                                                           | France        | 3.75° × ~1.9°                        |
| MIROC-ESM    | Japan Agency for Marine-Earth Science and Technology, Atmosphere and Ocean Research Institute (The University of Tokyo), and National Institute for Environmental Studies | Japan         | ~2.8° × 2.8°                         |
| MPI-ESM-LR   | Max Planck Institute for Meteorology (MPI-M)                                                                                                                              | Germany       | 1.875° × ~1.9°                       |
| NorESM1-M    | Norwegian Climate Centre                                                                                                                                                  | Norway        | 2.5° × ~1.9°                         |

Having estimated all of the factors needed for the RUSLE (Eq. (1)), we proceeded to calculate the current (2002–2016) soil erosion by water on the TP.

## 2.2. Comparison of current erosion with other assessments

The current estimates of soil erosion by water were compared to those derived by Yue et al. (2016), who based their estimates on the Second National Soil Erosion Survey of China and included topographical, land use and remote-sensing inputs in addition to field survey data. The Second National Soil Erosion Survey reported soil erosion grades are as follows: slight, light, moderate, intense, extremely intense, and severe, according to the Technological Standard of Soil and Water Conservation (SL190-2007), which was issued by the Ministry of Water Resources of China (Table 3). They did not use erosion rates because of the uncertainties in the input data and the model they used (Yue et al., 2016). To compare our results, the estimated mean soil erosion by water on the TP was converted into six erosion grades according to Table 3. For each of the erosion grades (except for the slight grade) in Table 3, the areas affected by soil erosion were calculated and then compared with those of Yue et al. (2016).

## 2.3. Spatial modelling and future prediction of soil erosion

We developed a MLR between our current *R* value and a set of climate, terrain and soil variables (Table 4) obtained from the WorldClim Data Portal (Hijmans et al., 2005), the SRTM DEM (Jarvis et al., 2008) and the Harmonized World Soil Database (HWSD, FAO/IIASA/ISRIC/ISSCAS/JRC, 2012), respectively. The WorldClim Data Portal provides a set of global-gridded bioclimatic variables with a spatial resolution of 1 km. There are 19 variables derived from monthly temperature and rainfall that represent annual trends, seasonality and extreme or limiting environmental factors (Hijmans et al., 2005).

The dataset (Table 4) used in the MLR was randomly separated into training and test sets. Two-thirds of the dataset were assigned to the training set, and the remainder was assigned to the test set. Additionally, the performance of different spatial models was assessed using 10-fold cross validations and boot-strap out-of-bag (OOB) samples on the training set. The final model, which produced the best statistics, was used to predict the independent test. The performance of the model that was finally used in this study was assessed using the statistical indexes of *R*<sup>2</sup>, RMSE, and ME.

In this study, a stepwise regression algorithm was employed to prevent overfitting the data and to identify the optimal regression model. The MLR coefficients were multiplied using climatic variables derived from the GCM scenarios for the year 2050 to produce future estimates of the *R* factor. The residuals of the MLR were added to these predictions to obtain our estimates of the *R* factor in 2050 on the TP at 1-km spatial resolution. Outputs of 19 bioclimatic variables from six GCMs (Table 5) in the CMIP5 were used to represent future climate factors. Two

extreme representative concentration pathways (RCP); RCP2.6 and RCP8.5 (Taylor et al., 2009), were used for investigating the climate projections over the TP. The GCM-derived bioclimatic variables, which were obtained from the WorldClim Data Portal (<http://www.worldclim.org/>), were downscaled and calibrated using WorldClim 1.4 by Hijmans et al. (2005). The final estimates of soil erosion by water in 2050 were derived using the predicted  $R$  factor in 2050 and other erosion factors ( $K$ ,  $LS$ ,  $C$ , and  $P$ ), which were indirectly affected by climate change in this study.

### 3. Results

#### 3.1. Current rate of soil erosion by water

Maps of the RUSLE factors on the TP are shown in Fig. 2. Areas without soil (cities, rocks, water bodies, permanent glaciers and salt crusts) were masked from the maps and were not included in the results. The predicted map of the annual  $R$  factor on the TP at 1-km spatial resolution is shown in Fig. 2a. The validation  $R^2$  and RMSE for the downscaled  $R$

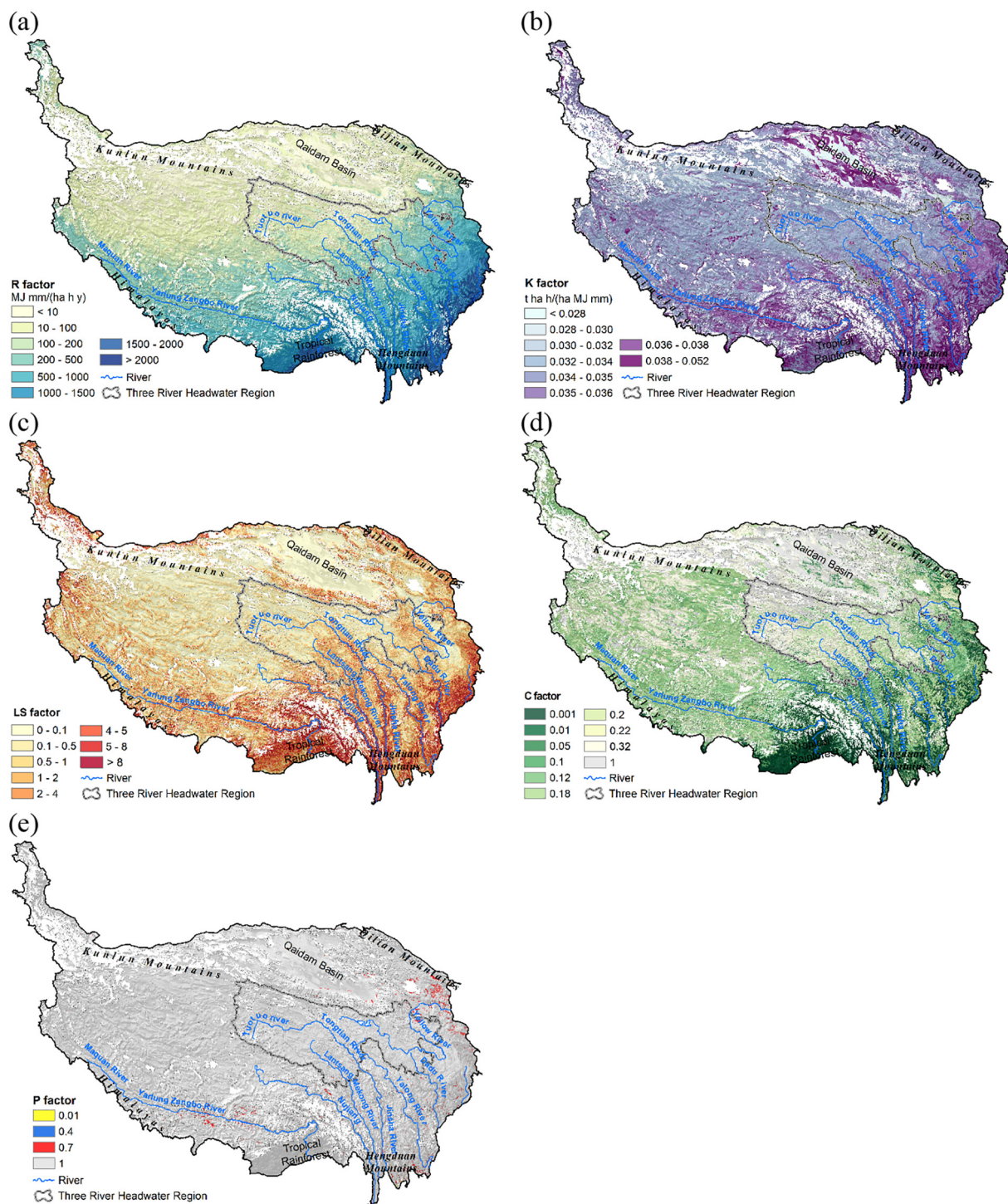


**Fig. 2.** Maps at a 1-km resolution of (a) rainfall erosivity,  $R$  factor; (b) soil erodibility,  $K$  factor; (c) slope length and steepness,  $LS$  factor; (d) cover management,  $C$  factor; and (e) support practice,  $P$  factor.

factor in the RK model were 0.88 and  $841.39 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ y}^{-1}$ , respectively. The mean annual  $R$  on the TP was  $309 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ y}^{-1}$ . The smallest values of  $R$  ( $<10 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ y}^{-1}$ ) were mostly observed in the northern part of the TP. The highest  $R$  value ( $>2000 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ y}^{-1}$ ) was observed on the southern TP, which is consistent with the subtropical monsoon and humid climate of this region. Our calculation of  $R$  compared favourably to the 35 testing rain gauges data, with an  $R^2 = 0.81$  and an RMSE =  $293.15 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ y}^{-1}$ .

The  $K$  factor map is shown in Fig. 2b. The validation  $R^2$  and RMSE for the  $K$  map were 0.58 and  $0.047 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ , respectively. The mean  $K$  value of the TP was  $0.034 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ . Fig. 2b shows that the least erodible soils ( $K$  values  $<0.028 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ) are found mostly in the low-lying desert regions with sandy soil, soil rich in calcium carbonate, soil with a cemented layer known as caliche (typically in the Qaidam Basin) and consolidated Pedocal soil, which is not easily detached and transported by overland flow. The most erodible soils ( $K$  values in the range of from 0.038 to  $0.052 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ ) were found mostly in forests or mixed vegetative cover areas, and sites on the southern and eastern TP. Alfisols and Semi-Alfisols (Chinese Genetic Soil Classification, Shi et al., 2004) had the largest  $K$  values (Fig. 2b).

Fig. 2c shows the  $LS$  factor map. On the TP, the mean  $LS$  factor value was 1.46. The lowest value  $LS$  factor ( $<0.1$ ) occurred in the lowest areas of the Qaidam Basin, while the highest value of  $LS$  factor ( $>8$ ) occurred in the Hengduan Mountains, southern Himalayas and tropical rainforest areas. Fig. 2c shows that the large  $LS$  values were consistent with high topography and coincided with the escarpments of the Himalayas and Hengduan Mountains, which rendered these areas extremely susceptible to erosion.

The  $C$  factor map is shown in Fig. 2d. The largest values of  $C$  occurred in the Qaidam Basin and the northwest part of the Three River Headwater Region in areas with no vegetation cover, whereas the smallest  $C$  values occurred in the evergreen broad-leaved forests within the tropical rainforest areas. The Kunlun Mountains, which are mainly covered by low-coverage grassland, and the cultivated land in the valley regions of the southern TP had relatively large  $C$  values. The western areas of the plateau, which are mainly covered by shrubs and steppe, had moderate  $C$  values.

The  $P$ -factor map is shown in Fig. 2e. It reflects a reduction in soil erosion caused by anthropomorphic impacts. On the TP, human engineering activities are limited and primarily focus on farmland, which has mainly occurred in the valley regions of the tropical forest areas, and on other woodlands, especially on all types of gardening areas.

The resulting RUSLE map of the annual rate of soil erosion by water on the TP is shown in Fig. 3a. On the TP, the average hillslope soil loss was  $2.76 \text{ t ha}^{-1} \text{ y}^{-1}$ , and the TP presented a potential annual soil loss of approximately  $559.59 \times 10^6 \text{ t}$  (Table 8). Areas in the east of the plateau showed the greatest erosion. Smaller rates ( $<1 \text{ t ha}^{-1} \text{ y}^{-1}$ ) were evident in the central and northern TP, particularly in the Qaidam Basin and the southern Kunlun Mountains (Fig. 3a).

Other woodlands, including recently afforested land, slash and all types of gardens, have the largest rate of erosion, but because of their limited areas on the TP, they have experienced relatively minor total soil loss. Median-coverage grassland and dry cropland have relatively large erosion rate, but the total soil loss under cropland is small (Table 8). The total erosion of grasslands (including median-coverage grassland, high-coverage grassland and low-coverage grassland) accounts for 90% of the total erosion on the TP. The erosion rate in land that is used for marsh, saline-alkali land and desert is relatively small. Paddy fields have the smallest rate of erosion, which might indicate that soil conservation practices have effectively reduced rates of erosion (Table 8).

Table 3 shows that erosion grade 1 (slight) areas account for the largest proportion of the total erosional area and primarily occur on the central and northern TP, whereas erosion grade 6 (severe) areas account for the lowest proportion of the total erosional area on the TP and primarily occur in the Hengduan Mountains and the border areas of the eastern TP (Fig. 3b).

### 3.2. Comparing soil loss estimates to other assessments

Fig. 4 presents a map of the areas that have been influenced by water erosion at different erosional grades on the TP and shows a comparison between our results and those of Yue et al. (2016). Compared to the estimates of Yue et al. (2016), we obtained greater estimates in the light and moderate erosion grades for counties on the southern plateau, and lesser estimates in counties of the northeastern plateau (Fig. 4). For regions of extremely intense and severe erosion, there were not marked differences between our estimates and those of Yue et al. (2016), although our estimates were greater in some regions of the southeastern TP.

### 3.3. Projected future soil loss potential on the Tibetan Plateau

The parameters of the MLR are provided in Table 6. In this section, stepwise regression was used to fit the regression model and choose predictive variables. With stepwise regression analysis the factor

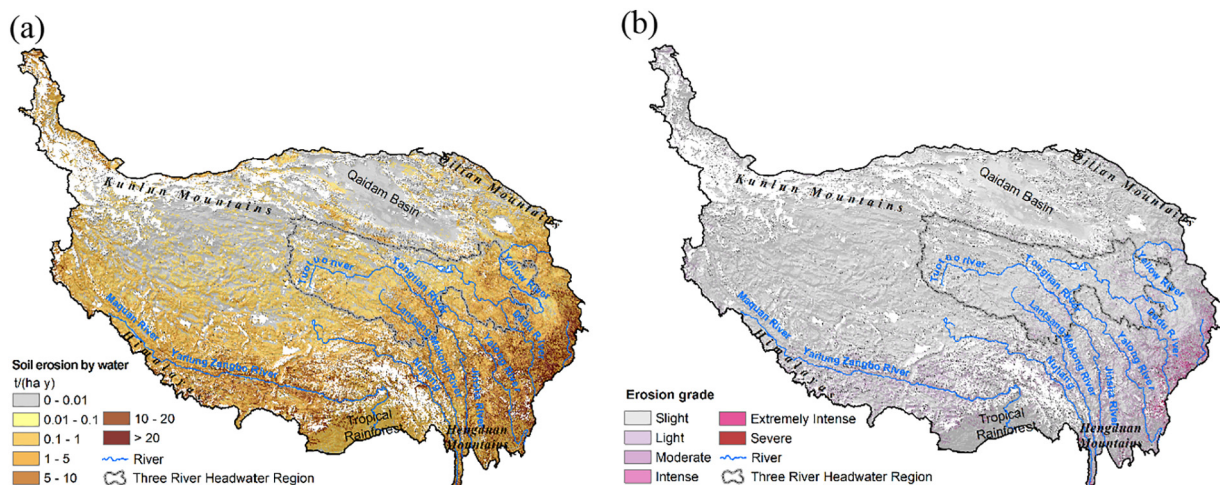


Fig. 3. Maps of (a) modelled current (2002–2016) annual soil erosion by water and (b) soil erosion grade at 1-km resolution in the Tibetan Plateau.

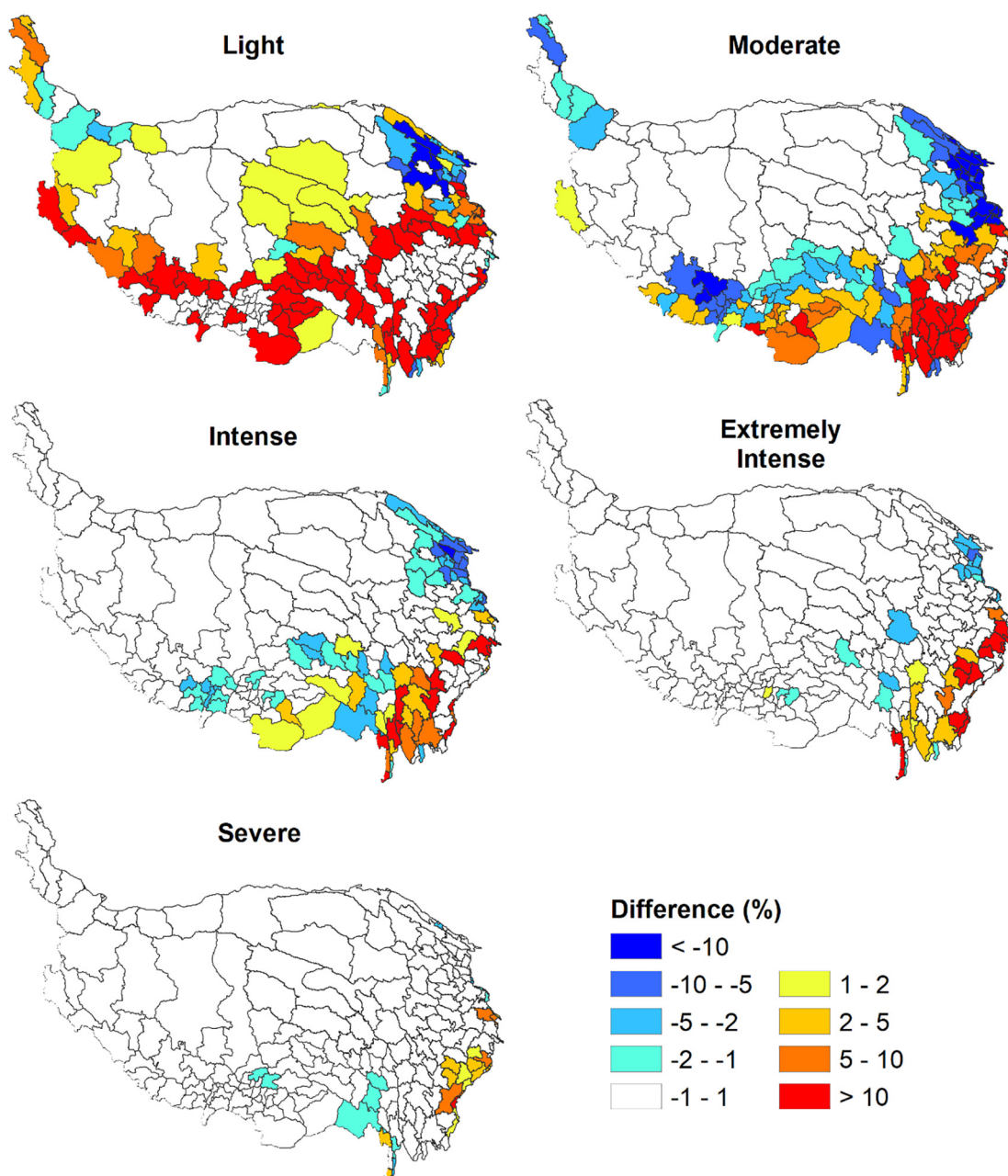


**Fig. 4.** Maps showing the differences between this study and Yue et al. (2016). The comparisons are made based on the areas that have been influenced by water erosion at different erosional grades on the Tibetan Plateau. Red represents a greater estimate in this study, and blue represents a lesser estimate in this study.

**Table 6**

The results of the stepwise MLR model. Note that the stepwise regression was used to fit the regression model and choose predictive variables.

| Coefficients | Estimate | Std. error | t value | Signif. codes | Coefficients | Estimate | Std. Error | t value | Signif. codes |
|--------------|----------|------------|---------|---------------|--------------|----------|------------|---------|---------------|
| Intercept    | −1765.00 | 11.77      | −149.96 | ***           | bio8         | −0.05    | 0.02       | −3.48   | ***           |
| DEM          | −0.06    | 0.00       | −104.61 | ***           | bio9         | 0.22     | 0.01       | 22.54   | ***           |
| Slope        | 1.81     | 0.01       | 148.93  | ***           | bio10        | 49.98    | 0.18       | 271.40  | ***           |
| Clay         | 1.98     | 0.02       | 101.41  | ***           | bio11        | −66.48   | 0.18       | −364.38 | ***           |
| Sand         | 0.34     | 0.01       | 39.97   | ***           | bio12        | 3.80     | 0.01       | 490.83  | ***           |
| Silt         | 0.19     | 0.01       | 14.71   | ***           | bio13        | 16.36    | 0.04       | 412.55  | ***           |
| toc          | −4.97    | 0.08       | −61.70  | ***           | bio14        | 82.88    | 0.20       | 407.59  | ***           |
| bio1         | 12.93    | 0.10       | 133.48  | ***           | bio15        | 1.03     | 0.01       | 71.77   | ***           |
| bio2         | −26.45   | 0.08       | −320.49 | ***           | bio16        | −12.37   | 0.04       | −335.06 | ***           |
| bio3         | 91.71    | 0.26       | 347.44  | ***           | bio17        | −32.07   | 0.11       | −284.24 | ***           |
| bio4         | −1.83    | 0.00       | −443.81 | ***           | bio18        | 0.81     | 0.03       | 28.52   | ***           |
| bio5         | 14.99    | 0.07       | 226.30  | ***           | bio19        | 1.26     | 0.05       | 27.69   | ***           |
| bio6         | −12.05   | 0.05       | −244.05 | ***           |              |          |            |         |               |

Significance codes: \*\*\*<0.001.

**Table 7**

10-fold cross validation, out-of-bag (OOB) and independent test set validation statistics for the multiple linear regression model. Assessment using the coefficient of determination ( $R^2$ ), the root mean square error (RMSE), and the mean error (ME).

|                             | $R^2$ | RMSE   | ME    |
|-----------------------------|-------|--------|-------|
| Cross-validation statistics | 0.859 | 164.08 | −0.02 |
| Out-of-bag statistics       | 0.857 | 164.55 | −0.16 |
| Test-set statistics         | 0.857 | 164.08 | −0.02 |

temperature annual range (bio7), which had little influence on the  $R$  factor, was excluded. Table 7 shows the validation statistics of the MLR modelling. The assessment statistics from the predictions of the test data set were near those from the 10-fold cross validations and the OOB statistics. The result suggested that the MLR model that we developed was robust and accurate ( $R^2 > 0.85$  for each of the validation). Fig. 5a shows the residual map of the MLR model. The Moran's  $I$  value of the residual map is 0.88 and indicates that the residual of the MLR model has an obvious spatial autocorrelation. The variogram of the residual map is shown in Fig. 5b.

The maps of the projected  $R$  factor and the corresponding potential soil erosion by water in 2050, according to six GCMs and two RCPs, are shown in Fig. 6a and b. Fig. 6a shows that the high  $R$  value in 2050 mainly occurs in the southeast tropical rainforest and border areas. Fig. 6b shows that soil erosion will mainly occur on the southern TP. Fig. 7a shows the major differences in the  $R$  factor in 2050 among six GCMs and two RCPs occurring on the central and southwestern plateau. The  $R$  factor in 2050 predicted by the climate scenarios of MIROC-ESM and NorESM1-M showed an increase on the central plateau, whereas that predicted by the climate scenarios of IPSL-CM5A-LR showed a decreasing tendency in most of these areas (Fig. 7a). The  $R$  factor in 2050 predicted by the climate scenarios of GFDL-CM3 and MIROC-ESM showed a decrease on the southwestern TP, while the climate scenarios of IPSL-CM5A-LR and MPI-ESM-LR showed an increasing tendency in most of these areas (Fig. 7a). From our estimates, the overall erosion rates in the south part of the plateau will increase in 2050 under the climate scenarios of BCC-CSM1.1, IPSL-CM5A-LR, MPI-ESM-LR and NorESM1-M by RCP2.6 and RCP8.5, whereas estimates using the climate scenarios of GFDL-CM3 and MIROC-ESM by RCP2.6 and RCP8.5 show a decrease in 2050 in these areas (Fig. 7b). The estimates of erosion rates in the northern Plateau show an overall increase in 2050 under the climate scenarios of BCC-CSM1.1, MPI-ESM-LR, MIROC-ESM and NorESM1-M by RCP2.6 and RCP8.5. The estimates of soil erosion remain stable in 2050 over the most of the central plateau and the southeast tropical rainforest areas, according to the six GCMs and two RCPs (Fig. 7b).

Table 8 lists the estimated current mean and total soil loss (with standard deviations) on the TP and our 2050 predictions for different land uses. The estimation in 2050 was the value averaged by the six GCMs. The average projected potential soil erosion by water, based on the six GCMs, on the TP in 2050 according to the RCP2.6 and RCP8.5 was 3.17 and 3.91 t ha<sup>−1</sup> y<sup>−1</sup>, respectively. The TP presented a potential annual soil loss of approximately 633.49 × 10<sup>6</sup> and 775.69 × 10<sup>6</sup> t in 2050, respectively. Other unused land and the Gobi desert showed the greatest relative change of soil erosion rates in 2050, according to RCP2.6 and RCP8.5, while paddy fields and other woodland showed the least relative change of mean soil erosion rates (Table 8).

#### 4. Discussion

Soil erosion on the TP is complicated and diverse, and it includes water erosion, freeze-thaw erosion, and wind erosion. Some studies have assessed soil erosion on the TP, especially wind erosion (Han et al., 2014; Rohrmann et al., 2013; Xie et al., 2017; Yan et al., 2005; Yan et al., 2001; Zhang et al., 2007a) and freeze-thaw erosion (Guo et al., 2017; Guo et al., 2015; Yi et al., 2013; Zhang et al., 2007b). However, as a remote area that is sensitive to climate variability, water erosion on the whole TP has been rarely reported quantitatively, and few research studies have provided a prediction of the future soil erosion risk on the TP. The work that we present here on the assessment and future prediction of soil erosion by water is timely because of changing climatic conditions that may increase the risk of soil and land degradation on the TP (Wang et al., 2017), which can also affect its unique biodiversity and ecology.

In this study, soil erosion by water on the TP is based on the RUSLE. Our estimates of soil erosion by water on the TP show more accuracy than those derived from previous assessments not only because of the new data source that was used to compute erosion factors but also because improved methodologies were incorporated into the calculation. The  $R$  factor in this study was calculated based on merged daily rainfall data with rigorous quality control. Teng et al. (2017) demonstrated that the improved estimates of the  $R$  factor showed higher accuracy than the simple interpolated gauge-based approach. The  $K$  factor that we modelled in this study was based on the comprehensive soil properties and environmental data sets currently available and geospatial methods.

Compared to Yue et al. (2016), who assessed erosion for the whole of China based on the Second National Soil Erosion Survey, our estimates are continuous and, at 1-km resolution, were made using modern geospatial modelling using the best available data and data specifically for the TP. The difference between our study and that of Yue et al. (2016) might be related to the different data sources for the erosion

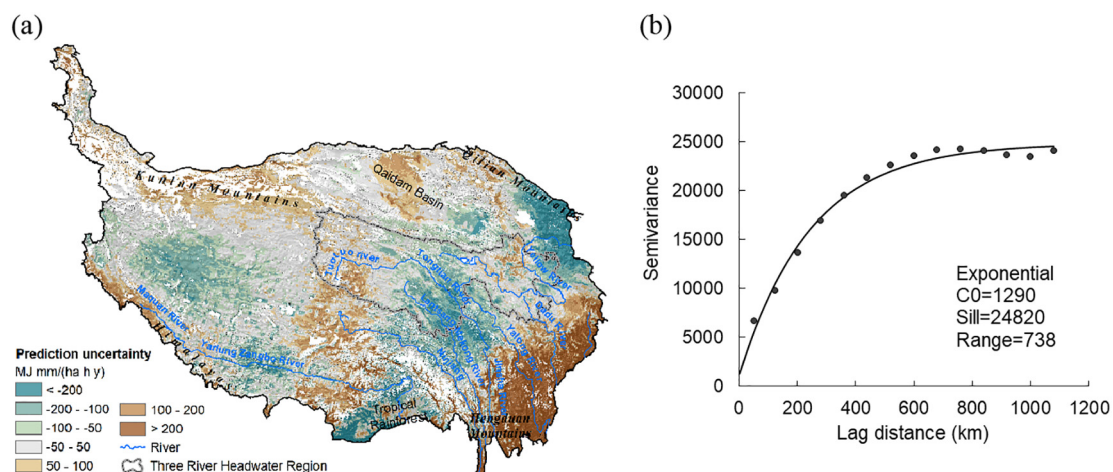


Fig. 5. Maps of the (a) residual of the MLR model and (b) its semi-variogram.

factor estimation, especially the  $R$  and  $K$  factors. The  $R$  value in [Yue et al. \(2016\)](#) was obtained using interpolation of the calculated  $R$  value on the rain gauge stations that were provided by the CMA. The accuracy of their estimates of  $R$  will depend on the spatial density of the interpolated rain gauges. However, these stations are unevenly distributed on the TP and very few are located in the southeast tropical rainforest areas. It may be for this reason that they estimated less erosion in the southeast areas of the plateau. Our  $R$  factor map was also derived using data from the CMA. However, our estimates of  $R$  are likely better because we first merged rainfall data from the rain gauges and the TRMM satellite and then downscaled  $R$  to produce estimates that are specific for the TP. The southeast tropical rainforest areas are influenced by a monsoon climate and have the highest amount of rainfall on the

plateau. A local study in southeast tropical rainforest areas conducted by [Fan et al. \(2013\)](#) confirmed the larger  $R$  values and reported that it is approximately  $12,189 \text{ MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ , which is similar to our results.

[Liu et al. \(2014\)](#) calculated the  $K$  values of all the soil types on the TP based on soil profile data and GIS. According to [Liu et al. \(2014\)](#), the  $K$  value on the TP ranges from  $0.026 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$  to  $0.039 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ , with a mean value of  $0.03 \text{ t ha h ha}^{-1} \text{ MJ}^{-1} \text{ mm}^{-1}$ . The highest value of  $K$  factor in [Liu et al. \(2014\)](#) occurred in the northeastern Qinghai Province, while the lowest value of  $K$  factor occurred in the Qaidam Basin. All these results are similar to ours. Our results are also consistent with [Wang et al. \(2004\)](#). [Wang et al. \(2004\)](#) showed that southeastern Tibet is more erodible

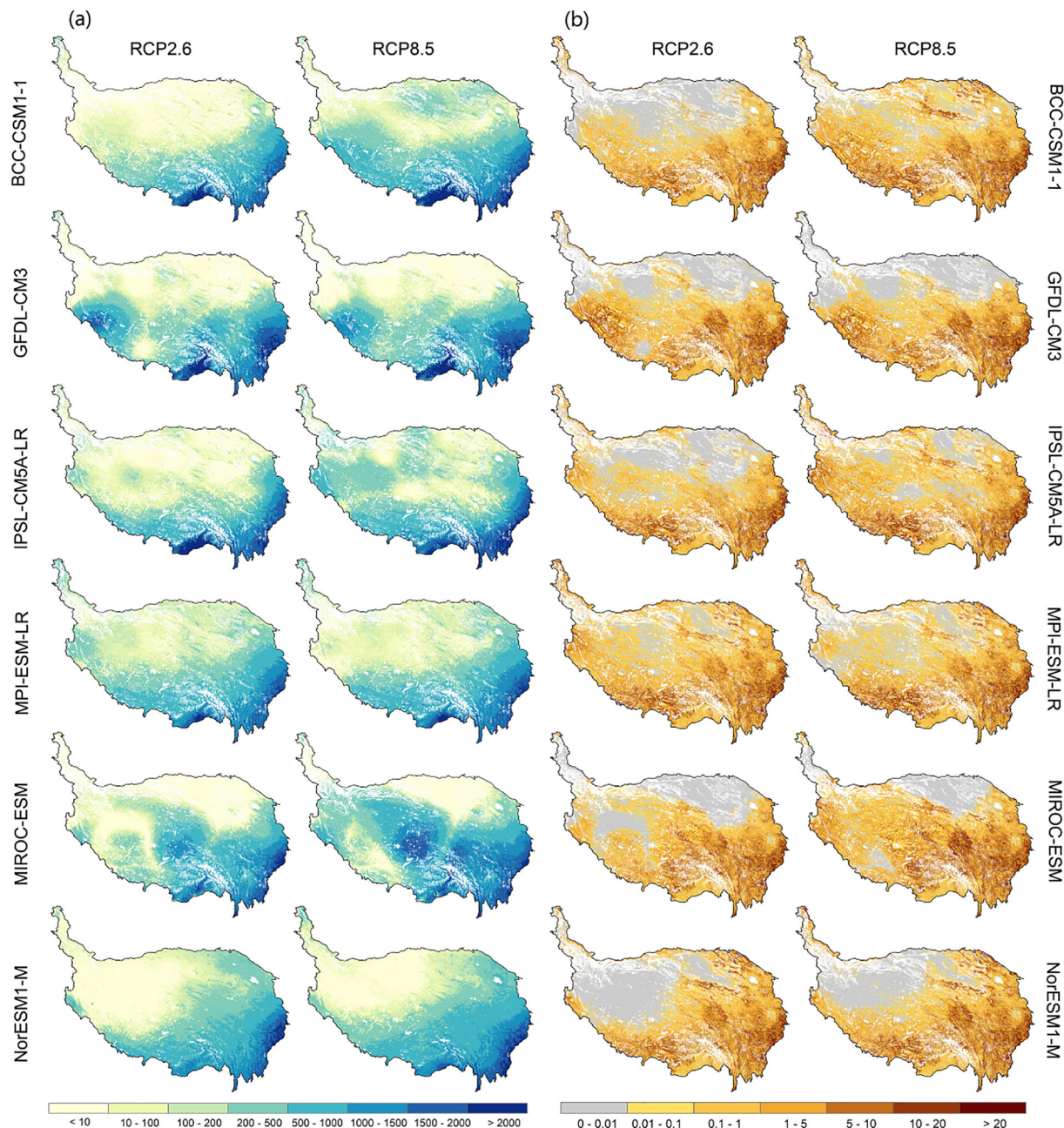


**Fig. 6.** (a) Maps of rainfall erosivity factor for 2050 by Climate Scenarios and Representative Concentration Pathways (RCPs). First row: BCC-CSM1-1 (RCP2.6, 8.5). Second row: GFDL-CM3 (RCP2.6, 8.5). Third row: HadGEM2-AO (RCP2.6, 8.5). Fourth row: IPSL-CM5A-LR (RCP2.6, 8.5). Fifth row: MPI-ESM-LR (RCP2.6, 8.5). Sixth row: MIROC-ESM (RCP2.6, 8.5). (b) Maps of potential soil loss for 2050 by Climate Scenarios and Representative Concentration Pathways (RCPs). First row: BCC-CSM1-1 (RCP2.6, 8.5). Second row: GFDL-CM3 (RCP2.6, 8.5). Third row: HadGEM2-AO (RCP2.6, 8.5). Fourth row: IPSL-CM5A-LR (RCP2.6, 8.5). Fifth row: MPI-ESM-LR (RCP2.6, 8.5). Sixth row: MIROC-ESM (RCP2.6, 8.5). Units of (a)  $\text{MJ mm ha}^{-1} \text{ h}^{-1} \text{ yr}^{-1}$ , and (b)  $\text{t ha}^{-1} \text{ yr}^{-1}$ .

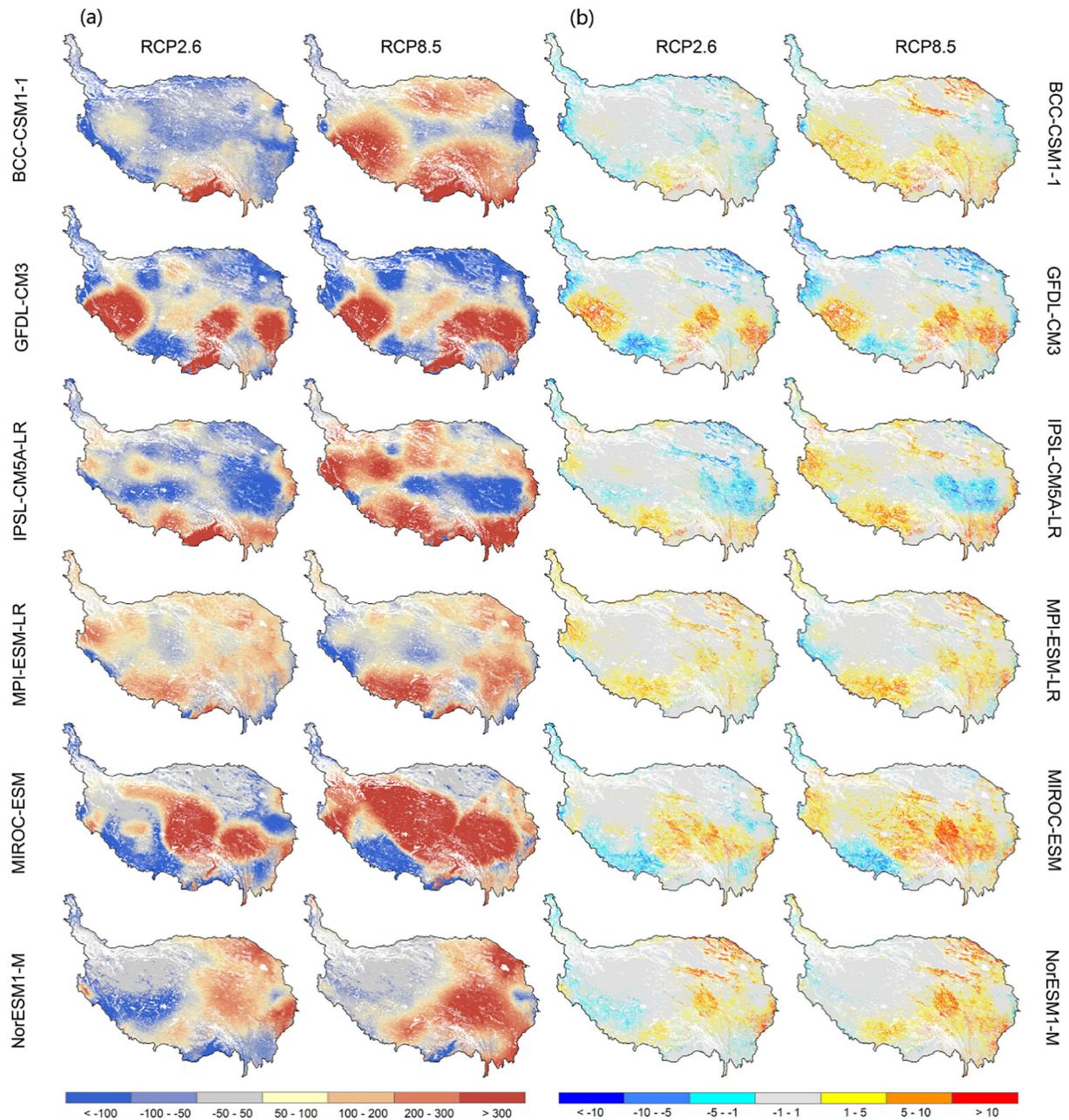


**Fig. 7.** (a) Change in rainfall erosivity factor for 2050 by Climate Scenarios and Representative Concentration Pathways (RCPs). First row: BCC-CSM1-1 (RCP2.6, 8.5). Second row: GFDL-CM3 (RCP2.6, 8.5). Third row: HadGEM2-AO (RCP2.6, 8.5). Fourth row: IPSL-CM5A-LR (RCP2.6, 8.5). Fifth row: MPI-ESM-LR (RCP2.6, 8.5). Sixth row: MIROC-ESM (RCP2.6, 8.5). The blue areas represent decreases, and the red areas represent increases in the rainfall erosivity value ( $\text{MJ mm ha}^{-1} \text{h}^{-1} \text{y}^{-1}$ ) compared to that of the current value. (b) Change in potential soil loss for 2050 by Climate Scenarios and Representative Concentration Pathways (RCPs). First row: BCC-CSM1-1 (RCP2.6, 8.5). Second row: GFDL-CM3 (RCP2.6, 8.5). Third row: HadGEM2-AO (RCP2.6, 8.5). Fourth row: IPSL-CM5A-LR (RCP2.6, 8.5). Fifth row: MPI-ESM-LR (RCP2.6, 8.5). Sixth row: MIROC-ESM (RCP2.6, 8.5). The blue areas represent decreases, and the red areas represent increases in potential soil loss ( $\text{t ha}^{-1} \text{y}^{-1}$ ) compared to that of the current value.

than northwestern Tibet. Most areas of the TP have a relatively small value of  $K$ .

According to our result, land that is covered by forest (especially sparse forest and shrub forestland) has experienced moderate erosion rates. However, this result showed inconsistency with other researchers. Garcia-Ruiz et al. (2015) undertook a meta-analysis of published soil erosion data from >4000 sites worldwide and showed that forests have relatively low erosion rates. Panagos et al. (2015) estimated soil loss by water in Europe in 2010 and found that forests have the lowest rate of soil loss. Chen et al. (2017) reviewed the effects of terracing practices on water erosion control in China based on meta-analysis and confirmed that terracing with forests resulted in the greatest

efficiency of runoff reduction. This inconsistency between our results and other studies can be attributed to the specific geographical characteristics of the TP. Forest on the TP is mainly distributed in areas with precipitation >400 mm annually (Zhao et al., 2015). These areas mainly occur on the southern TP at high elevations and in steep terrain. Thus, forest in these areas usually has high  $R$  and  $LS$  values, explaining the high rate of soil erosion.

Downscaling methods have been employed in former studies to assess the impact of climate change on soil erosion (Li and Fang, 2016). Among them, regression models, which have the characteristics of low computational requirements and ease of implementation, can be regarded as the most popular methods. In this study, MLR was used to

**Table 8**Estimates of annual potential soil loss on the Tibetan Plateau by land use type currently and in 2050 (Units:  $\text{t ha}^{-1} \text{y}^{-1}$ ;  $\text{t} \times 10^6 \text{y}^{-1}$ ).

| Land use                  | Description                                                       | Current |       |        | RCP2.6 (2050) |       |        |                 | RCP8.5 (2050) |       |        |                 |
|---------------------------|-------------------------------------------------------------------|---------|-------|--------|---------------|-------|--------|-----------------|---------------|-------|--------|-----------------|
|                           |                                                                   | Mean    | SD    | Total  | Mean          | SD    | Total  | Relative change | Mean          | SD    | Total  | Relative change |
| Other woodland            | Recently afforested land, slash, all types of garden              | 16.14   | 21.19 | 1.90   | 16.36         | 20.92 | 1.90   | 1.37            | 18.44         | 22.94 | 2.13   | 14.23           |
| Median-coverage grassland | Grassland with a coverage between 20% and 50%                     | 4.42    | 12.99 | 242.59 | 4.83          | 13.77 | 262.93 | 9.17            | 5.58          | 14.66 | 302.33 | 26.10           |
| Dry cropland              | Rainfed cropland without a water supply and irrigation facilities | 4.42    | 9.76  | 7.83   | 4.65          | 10.16 | 8.18   | 5.29            | 5.06          | 10.75 | 8.84   | 14.48           |
| Bare soil                 | Land covered with soil, vegetation coverage < 5%                  | 4.13    | 29.03 | 1.93   | 4.68          | 29.74 | 2.15   | 13.32           | 5.59          | 30.16 | 2.55   | 35.25           |
| High-coverage grassland   | Grassland with a coverage > 50%                                   | 3.73    | 8.14  | 152.48 | 4.19          | 8.88  | 169.62 | 12.16           | 4.95          | 9.70  | 199.16 | 32.55           |
| Other unused land         | Other unused land, including alpine deserts and tundra.           | 2.45    | 12.05 | 19.23  | 4.47          | 14.40 | 34.72  | 82.88           | 7.88          | 16.94 | 60.85  | 222.30          |
| Low-coverage grassland    | Natural grassland with a coverage of 5%–20%                       | 2.22    | 10.01 | 112.21 | 2.64          | 10.74 | 130.31 | 18.74           | 3.48          | 12.38 | 170.60 | 56.33           |
| Sparse forest             | Woodland with a crown density of 10%–30%                          | 1.45    | 1.70  | 3.38   | 1.56          | 1.78  | 3.61   | 7.33            | 1.66          | 1.87  | 3.85   | 14.45           |
| Shrub forestland          | Scrubland with a crown density > 40% and a height < 2 m           | 1.21    | 1.63  | 11.20  | 1.28          | 1.70  | 11.78  | 5.84            | 1.40          | 1.79  | 12.82  | 15.72           |
| Sandy land                | Land covered with sand, vegetation coverage < 5%                  | 0.34    | 3.37  | 1.62   | 0.42          | 3.62  | 1.86   | 23.98           | 0.63          | 4.59  | 2.74   | 83.17           |
| Dense forest              | Woodland with a crown density > 30%                               | 0.20    | 0.17  | 2.97   | 0.22          | 0.18  | 3.24   | 9.41            | 0.24          | 0.20  | 3.52   | 18.79           |
| Gobi desert               | Stony and alpine deserts with a vegetation coverage < 5%          | 0.17    | 0.94  | 1.57   | 0.25          | 1.11  | 2.31   | 47.75           | 0.53          | 1.67  | 4.86   | 214.38          |
| Saline-alkali land        | Land with more salt on top soil                                   | 0.12    | 1.04  | 0.45   | 0.21          | 1.38  | 0.62   | 71.59           | 0.38          | 2.17  | 1.12   | 211.65          |
| Marsh                     | Land with accumulated water and hygrocous plants                  | 0.10    | 0.53  | 0.22   | 0.13          | 0.65  | 0.26   | 31.26           | 0.16          | 0.76  | 0.32   | 61.66           |
| Paddy fields              | Flooded parcel of arable land used for growing semiaquatic rice   | 0.09    | 0.12  | 0.00   | 0.09          | 0.13  | 0.00   | 2.32            | 0.10          | 0.14  | 0.00   | 12.82           |
| TP                        | Tibetan Plateau                                                   | 2.76    | 9.77  | 559.59 | 3.17          | 10.54 | 633.49 | 14.86           | 3.91          | 11.64 | 775.69 | 41.67           |

Relative change =  $(\text{Mean}_{2050} - \text{Mean}_{\text{current}}) / \text{Mean}_{\text{current}} \times 100$ .

calculate the future  $R$  factor by testing the relationship between current  $R$  values and environmental factors and to project them into 2050 using the same regression coefficients. The soil erosion risk in 2050 was then predicted by the changing  $R$  factor in 2050. The approach in this study is similar to that used by Yigini and Panagos (2016), and it assumes that erosion, especially the erosion factor of rainfall erosivity, is largely governed by climate.

Future soil erosion prediction for the TP, using six models with respect to the regional climate, indicate that the southwestern TP appears to be an area that is more sensitive to the climate change in 2050, especially if the conditions of scenario RCP8.5 occur, corresponding to the pathway with the largest climatic variability and the highest greenhouse gas emissions. This area is largely affected by westerlies and the monsoon with significant precipitation occurring during the wet season. Su et al. (2016) suggested that this area is more likely to experience future temperature increases compared to other regions on the TP. Changes in runoff across this area are closely linked to temperature and precipitation increases. The increasing trend of soil total runoff for this area under the scenarios of RCP2.6 and RCP8.5 indicate the future erosion risk in 2050. The occurrence of increased soil erosion by water may influence local ecosystems on the TP and, hence, induce hydrologic variations in the rivers originating from the plateau, such as the Yangtze, Yellow and the Lantsang-Mekong rivers.

There are some limitations to our approach, and there are also sources of uncertainty influencing our results. The  $C$  factor in this study is related to the land use type. Conventionally,  $C$  factor is calculated as a product of canopy cover, canopy height, residual cover, below-ground biomass and time. However, these factors are difficult to measure for the whole TP. The method that we used in this study to measure the  $C$  factor might not be fully capable of illustrating the content of the  $C$  factor and might induce some uncertainty in our results. There are also some uncertainties that occurred in the procedures of the  $R$  downscaling and  $K$  mapping. These uncertainties will remain in the following calculation of soil erosion by water. We used two emission scenarios for future projections that fall on the lowest and highest end of all warming scenarios. However, how much warming will actually occur on the TP is still uncertain. The results of soil erosion predicted by the six GCMs provide different trends in some regions of the TP, and this is reflected in the high uncertainty of predicted future soil erosion. The

six GCMs and two scenarios that we used here were an attempt to avoid a larger part of the model bias. We believe the scenarios and projection models that we used provide a useful soil erosion threshold in 2050.

## 5. Conclusions

The TP has been demonstrated to be a sensitive area to climate change. Quantifying the impacts of climate change and its effect on soil erosion over the TP is important to assist policy-makers and land managers in adopting strategies for its protection and conservation. However, reported quantitative observations of water erosion on the TP are limited.

This study produced the best estimates of current (2002–2016) erosion on the TP using RUSLE based on the most current and available data sets. Improved methodologies were applied to calculate the erosion factors of  $R$  and  $K$ . An MLR model was developed between the current  $R$  value and the sets of climate, terrain and soil variables to predict the  $R$  factor value and erosion in 2050.

We found that the average soil erosion by water on the TP is  $2.86 \text{ t ha}^{-1} \text{y}^{-1}$ , which equates to potential annual soil losses of  $559.59 \times 10^6 \text{ t}$  over this area. Areas that suffer from severe soil erosion occur in the Hengduan Mountains and the southeastern Himalayas. Land that is under other woodland has the highest erosion rate because of their high altitude and strong vertical zonality. Our estimates of current erosion are comparable to those made by other researchers.

Our prediction of soil erosion in 2050 suggests an increase under the six future climate models and two RCPs. The average projected potential soil erosion by water on the TP in 2050 according to the RCP2.6 and RCP8.5 was  $3.17$  and  $3.91 \text{ t ha}^{-1} \text{y}^{-1}$ , respectively, which equates to potential annual soil losses of  $633.49 \times 10^6 \text{ t}$  and  $775.69 \times 10^6 \text{ t}$ , respectively. The main differences between erosion rate according to the RCP2.6 and RCP8.5 were on the eastern and southeastern TP. Water and soil conservation measures over the TP should be continued and strengthened. The southwestern TP and areas with steep slopes and high altitudes are more sensitive to climate variability; therefore, the increased risk of soil erosion in these areas should be further studied.

The methods that we used in this study were useful for characterization of soil erosion by water over a large area. As it can process data

input for large regions with sparse data, RUSLE can provide quantitative estimates of long-term soil erosion by water on the TP. The method that we used, which incorporated a regression model, climate models and scenarios, can provide a threshold of future soil erosion rates in 2050 with low bias. The results of this study should be useful for the development of regional and national policy on soil conservation and environment protection.

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